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# A multi-method simulation approach for evaluating the effect of the interaction of customer behaviour and enterprise strategy on economic viability of remanufacturing

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The economic viability of remanufacturing is shown to be significantly affected by the interaction between customer behaviour and strategic decisions of the manufacturer. The paper investigates this interaction using a multi-method simulation model combining a multi-agent-based model of customers and a system dynamics based model of the remanufacturing enterprise. The model uses validated approaches for each component and is used to investigate, analyse and forecast the long-term effects of strategic decisions of the remanufacturing enterprise on customer behaviour and the consequent effects on the business environment that determine the profitability of the enterprise.

Lifecycle; Simulation; Remanufacturing

## 1. Introduction

Remanufacturing is widely recognized among the most profitable and resource efficient options for implementing the circular economy paradigm at industrial level, since it targets the recovery and reuse of functions and materials from post use-products [1]. It is defined as the set of operations for returning a used product to, at least, its original performance with a warranty that is equivalent or better than that of the newly manufactured product [2]. The benefits of remanufacturing are particularly relevant in the scenario where the manufacturer exploits its product knowledge to offer a remanufactured product to the aftermarket, at more affordable economic conditions.

A typical example of this scenario is the automotive industry, where the aftermarket volumes create significant business opportunities for remanufacturing. In spite of the business attractiveness of remanufacturing and the growing interest towards circular economy, making a transition to new remanufacturing businesses is perceived as a high-risk opportunity for manufacturers, mainly due to the significant sources of uncertainty and the relatively long-term horizon of profit returns. Uncertainties mainly relate to the accessible post-use volumes, the post-use product conditions, the technical dismantling aspects as well as the customers' acceptance of remanufactured products, which strongly affect the remanufacturing system profitability. As a consequence, capturing the dynamics and inter-dependence of these variables over time and their mutual effect on the effectiveness of remanufacturing decisions into a comprehensive model would be a fundamental asset for manufacturers in their transition to sustainable remanufacturing businesses, ultimately boosting circular economy at large scale.

This paper proposes a novel approach for assessing the interaction of parameters that affects production systems at different points in the product lifecycle and shows the effective application of this approach to remanufacturing where the insight can be used for effective investment strategy setting [3]. The proposed approach is based on multi-method simulation and combines the versatility and fidelity of agent-based simulation with the strategic acuity granted by system dynamics.

Traditionally, simulation in manufacturing systems is carried out using one of the three fundamental methods, namely Discrete Events Simulation, System Dynamics and Agent Based Simulation [4]. These methods have been individually applied across the lifecycle of manufacturing and remanufacturing systems but little work has been carried out in simulation of interactions between system variables across different phases of the later stages of the lifecycle, in a dynamic manner [5] with the notable exception of the work carried out by Umeda and colleagues who mainly focused on environmental analysis and product design [6]. The challenge presented by such cross-phase interactions is that each of the individual approaches is suitable for modelling certain aspects of each phase. For example, system dynamics has been shown to be an excellent method for modelling and analysis of strategies and long-term policies and their effects on production. Agent based models, on the other hand, provide a framework for describing diverse behaviours. The decision mechanisms of customers can thus be captured with a much greater fidelity in agent-based modelling compared to other approaches.

Hence, none of these approaches can, in isolation, provide a good solution to simulate mutual interactions across different phases. A suitable alternative would be to combine multiple simulation approaches in a single framework to benefit from the advantages of each approach for each phase in the lifecycle. The combination of system dynamics and discrete events methods is presented as hybrid simulation and is well explored in the literature but studies in remanufacturing combining agent-based techniques with the other two are rare [7].

In the remaining sections of the paper, the fundamentals of multi-method simulation are explored and the logic of system dynamics and agent-based modelling are explained to provide an overview of how the two are linked together. The proposed approach is applied to remanufacturing as a problem that spans multiple phases of the lifecycle. The resulting multi-method model is simulated to show how this approach can be used to analyse and forecast long-term interactions of variables in each phase of the system lifecycle. Finally, the results are used to draw conclusions about the applicability of the proposed approach to the circular economy.

## 2. Overview of the multi-method simulation approach

The proposed multi-method model for remanufacturing is based on the integration of system dynamics, modelling the strategic and operational aspects of the remanufacturing business scenario, and agent-based simulation, modelling the customer behaviour towards newly manufactured and remanufactured products. Their basic features are discussed in the next sections.

### *2.1. System Dynamics (SD)*

In *SD*, the system is described in terms of flows that are integrated in stocks. This results in formation of differential equations that are solved using numerical methods. There is a general assumption of continuity in the values of variables in this method, so sudden changes in variables can introduce simulation artefacts, fragile models and unreliable results. The methodology is good for observing trends over time rather than individual values. As a result, it is an excellent approach for modelling policies and assessing causes and long-term effects of parameter and structure changes. When applied to remanufacturing this method can provide a validated aggregate view of the production system without excessive detail [7].

### *2.2. Agent Based Modelling (ABM)*

In *ABM,* the participating entities in the production system are modelled as distinct units that interact with each other, exchange messages and pursue their individual goals. Agents are independent software entities that are executed in parallel and generally reside in the same virtual space. Each agent can be given a set of goals to pursue. Multi-agent systems are thus difficult to control, basically due to emergent behaviour. Modelling using agents is appropriate when various behaviours are expected from the same type of entity. Multi-agent models are most powerful when the various entities communicate with each other; “messages” are used to model these interactions. Previous research has shown that this approach can be successfully used in modelling customer behaviour [8, 9].

### *2.3. Combining the two models in a single framework*

In order to effectively combine multi-agent simulation with system dynamics, there are two potential approaches: manipulate agent variables in the system dynamics model or vice versa. Manipulation of agent variables in the system dynamics model is difficult and will require elaborate coding of manipulations for each individual agent as well as potential introduction of non-continuous elements in the model that could lead to derivation difficulties. As a result, manipulation of system dynamics models by the agents is the more promising approach for linking the two methods. Care should be taken not to introduce discontinuities into the system. Anylogic, a Java based simulation software, provides an environment for multi-method simulation and allows the manipulations to be carried out in a computationally safe manner. It has thus been chosen to test the proposed approach.

## 3. Description of the model

### *3.1. Modelling the remanufacturing system*

The system dynamics model in Figure 1 is used to create a simple model of remanufacturing production systems without loss of generality; it is inspired by the method proposed in [8].
The main stocks in the model are: 1. The backlog of factory orders for remanufactured products (*RemanBacklog*) 2. The remanufactured stock that has been produced (*RemanProducedStock*); and, 3. The remanufacturing capacity of the factory (*Remanufacturing Capacity*). The remanufacturing production flow (*RemanProduction*) connects the backlog stock to the produced stock. The remanufacturing capacity is adjusted by the flow that represents the building of new facilities and hiring additional workforce (*CapacityBuilding*). Two parameters define the delays that exist in the dynamic system: *FactoryExpansionDelay* defines how long it will take the enterprise to increase the capacity by one production unit per time unit (which has been selected as weeks in this instance), *ManufacturingLeadTime* defines the time that it takes for a remanufactured product to be produced. It is assumed that product delivery is instantaneous. The decision variable representing the production policy is the stock coverage that the enterprise wishes to maintain: *TargetLeadTime* defines the length of time within which the enterprise would like to clear the backlog at any given time. A lower value for this variable would mean an increase in the capacity and hence lower work in progress but higher investment costs. A higher value would mean that customers will have to wait before they get their orders delivered. *TargetLeadTime* can, at best, be equal to *ManufacturingLeadTime* which is the time that it takes to physically perform all production steps in the remanufacturing process. Thus, the important aspects of the model can be mathematically summarised as:

$$RPS = \int \min\left(\frac{RB}{MLT}, RC\right) dt \tag{1}$$

Where $RPS$ is the remanufactured product stock, $RB$ is the backlog of orders for remanufactured products, $MLT$ is the manufactured lead times and $RC$ is the remanufacturing capacity of the factory. The remanufacturing capacity expansion is modelled by:

$$RC = \int \max\left(\frac{\frac{RB}{TLT} - RC}{FED}, 0\right) dt \tag{2}$$

Where $FED$ is the time it takes for investment in capacity expansion to yield results and $TLT$ is the target lead time decided by the enterprise strategy. This creates the simplest non-trivial example of a non-linear dynamics system to enable the effect of strategies to be modelled in the remanufacturing system. The assumption is that the remanufactured product is competing with a newly manufactured alternative. Whilst the manufacturing system of the alternative can be modelled in a similar manner, it may be assumed that its dynamics are well recognised, and a simple delay (*AltDelay*) can be used to approximate the alternative production system without loss of generality.

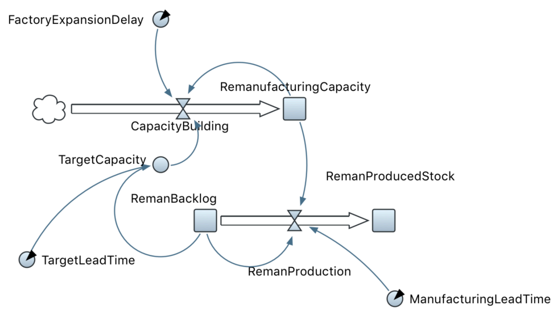


**Figure 1.** System Dynamics model of the remanufacturing system

### *3.2. Modelling customer behaviour*

Generally speaking, costumers behave in similar but different manners. In remanufactured products, several factors have been identified that influence customer behaviour. Examples of studies of customer behaviour in remanufacturing include prediction of product returns [11], reverse logistics [12] and prediction of consumers storage and utilisation behaviour [13]. Agent based modelling is thus used to create a representative behaviour model of customers with memory and interaction.

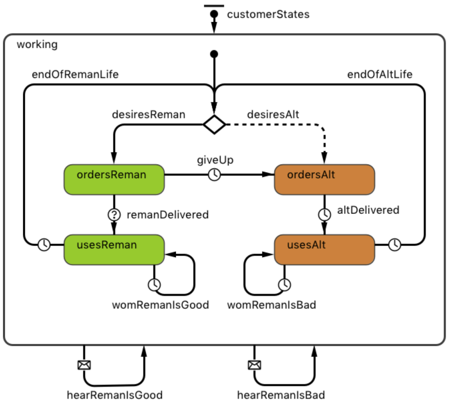

**Figure 2.** Agent based model of the customer

Examples of three key aspects are modelled, namely: initial desires, historical awareness and change of behaviour as the result of communication with other customers. The main states are as follows: the customer has ordered remanufactured products and is awaiting the availability of stock (*ordersReman*); the customer has received delivery of the remanufactured stock and is using it (*usesReman*); the customer has ordered the alternative product (*ordersAlt*); and the customer has received delivery of the alternative product and is using it (*usesAlt*).

When the customer agent is created, the initial transition stochastically branches based on the customers preference for remanufactured products (*desireForReman*). If the remanufactured branch is chosen, the customer orders the remanufactured product. Each customer will only wait for a given amount of time (*patience*) for availability of product. If remanufactured products are unavailable, the customer will give up waiting (*giveUp*) and orders the alternative product which will be delivered in a fixed time as the alternative manufacturing system is modelled as a fixed delay.

The historical insight of customers is captured by increasing their patience whenever remanufactured products are delivered on time and decreasing it when they give up waiting for the delivery of products. The communication aspect is captured by customers interacting with each other by spreading the word of mouth. If they use remanufactured products they will tell other customers that remanufactured products are good (*womRemanIsGood*). If they use the alternative products they will let others know that the alternative product works well and spread the word of mouth against the remanufactured product (*womRemanIsBad*). When the recipient of a message hears the good word of mouth about remanufactured products their desire for purchasing remanufactured products increases (*hearRemanIsGood*) and when they hear that alternative products are better than the remanufactured product their desire decreases (*hearRemanIsBad*).

### *3.3. Linking the models together*

The link between the two aspects of the simulation is defined by manipulating the stocks in the system dynamics section of the model in state transitions of the agents representing customers. Whenever the customer enters the *ordersReman* state, the value of the stock *RemanBacklog* is increased by the order quantity associated with that customer. The customer can only transition to *usesReman* if there is sufficient stock to fulfil their order in *RemanProducedStock*. When the transition occurs, the order quantity for that customer is removed from the *RemanProducedStock* in the system dynamics model. The presence of the minimum delay of *ManufacturingLeadTime* in equation (1) ensures that the continuity of the system dynamics model is preserved, and simulation artefacts are avoided.

## 4. Experimental analysis and numerical results

In order to demonstrate the effectiveness of the proposed methodology, a test case has been defined in cooperation with an automotive part remanufacturer. It is assumed that the overall demand for the parts over the simulation period remains constant [14]. The remanufactured product manufacturer is selling their products to 1000 potential dealers who require between 3000 and 10,000 products in each order (in multiples of 1000). Each dealer sells their stock in 10 weeks after receiving the delivery. For each dealer, the desire to order a remanufactured product is initially defined as the being the same as ordering the alternative newly manufactured product. The initial patience for each dealer is a random variable with a normal distribution with a mean of 2 weeks and standard deviation of 0.3 weeks. The manufacturing lead time and alternative product manufacturing delay are both defined as two weeks. The initial remanufacturing capacity is 20,000 units per week and an initial backlog of 10000 units is assumed. It is assumed that no remanufactured stock is initially available.

Each dealer meets another dealer every week and spreads the word of mouth about the product that they are selling. On every occasion of hearing good word of mouth about the remanufactured product increases the dealer's desire to purchase it by 20%. Bad word of mouth, decreases their desire to purchase remanufactured products by 25%. Giving up on waiting for remanufactured product delivery, decreases the dealer's patience by 10% and timely delivery increases it by 5%.

The policy variable of target lead time is set to 2, 4 and 6 weeks and the model is simulated for 100 weeks to produce results that reflect the customer behaviour as well as an indication of the economic viability of remanufacturing. The runtime environment of the simulation is shown in Figure 3.

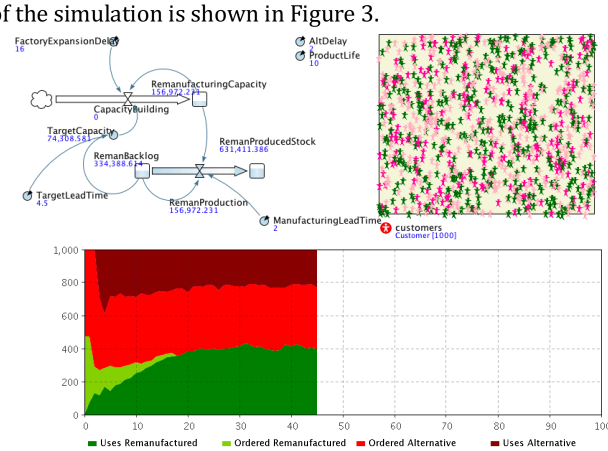

**Figure 3.** The Anylogic multi-method simulation environment at runtime

In Figure 4, the results for the target lead time of 2 weeks are shown. The graphs show the state of dealers over the 100 weeks, the cumulative spread of good and bad word of mouth, and the cumulative investment in expansion of remanufacturing facilities. The results in Figure 4 indicate that the policy of targeting a lead time of 2 weeks for the remanufacturing enterprise would enable it to take over the market in around 2 years but will need an investment for more than 400,000 units per week in production capacity. Figure 5 shows the results for the target lead time of four weeks. Again, the company would be able to assume a commanding position in the market in 100 weeks, but the required investment over the same period is equivalent to creating facilities to produce 250,000 units per week, around half that of the first scenario. It is noticeable that the bad word of mouth which used to be much lower than the good word of mouth in the previous scenario is now around half of the good word of mouth. 4 weeks is thus a better target for the company.

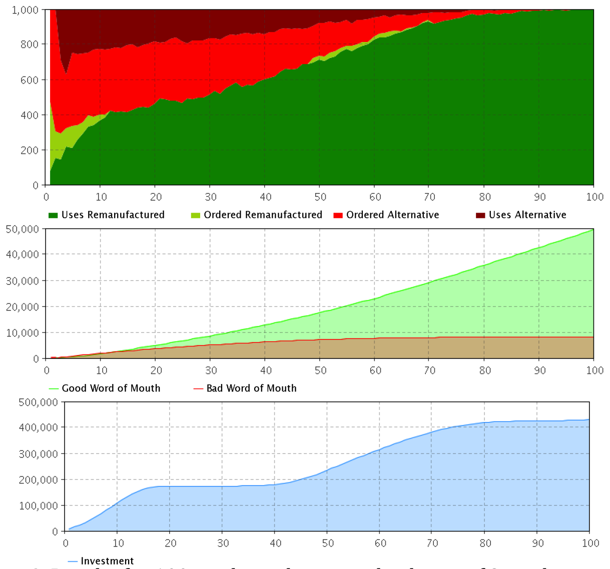

**Figure 4.** Results for 100 weeks with a target lead time of 2 weeks.

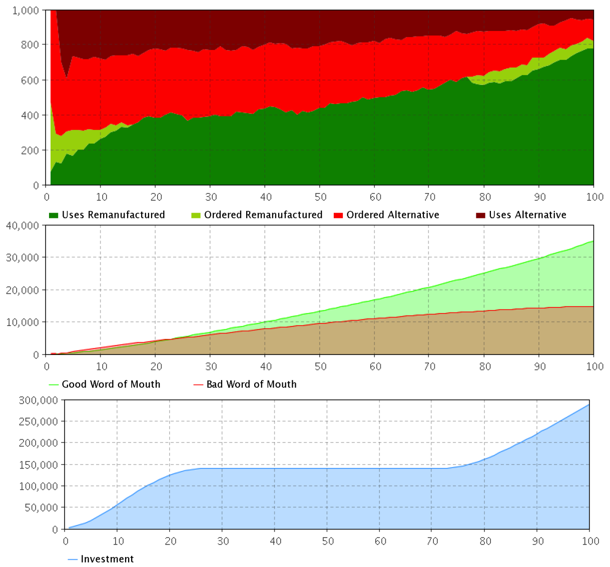

**Figure 5.** Results for 100 weeks with a target lead time of 4 weeks.

The results for the target lead time of 6 weeks, shown in Figure 6, demonstrate how the mutual effect of company policy and customer behaviour can become detrimental to the economic viability of the company. The strategy of slowly building up the capacity to produce the remanufactured stock requires less investment but the bad word of mouth exceeds the good word of mouth and most customers start favouring the alternative new product. The remanufacturing company loses market share and without the good word of mouth to encourage new buyers, the market share shrinks more rapidly leading to losses.

## 5. Conclusions

Combining multi-agent simulation and system dynamics is shown to allow the dynamics of interactions between different lifecycle phases to be captured effectively. This provides a framework for dynamic modelling of customer preference based on historical experience, shaping of opinions based on word of mouth and the remaining uncertainty in customer behaviour to be analysed in conjunction with strategies that affect production lead times and capacities. Complex psychological and sociological for individual decision taking processes and interactions can be modelled on top of this framework as needed in the future.

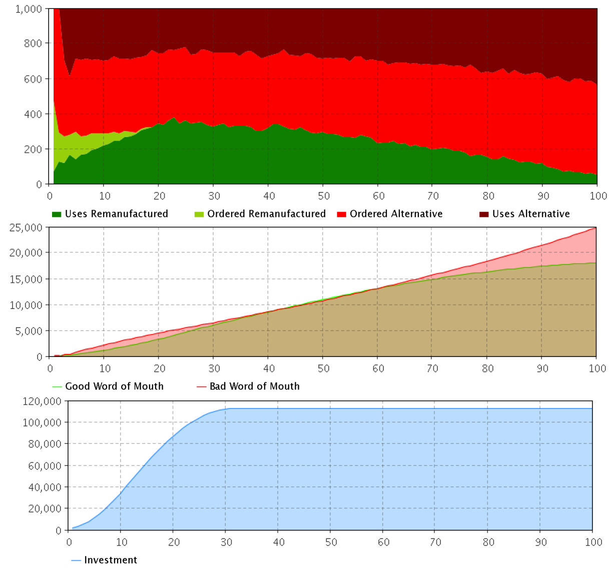

**Figure 6.** Results for 100 weeks with a target lead time of 6 weeks

The produced model clearly shows that the interaction between the two aspects can result in critical thresholds in decision variables that can have a major effect on the economic viability of remanufacturing operations. For example, the model in the paper would be able to provide the automotive company with a suitable range for target lead times to make remanufacturing viable. The proposed methodology can be applied to many manufacturing problems beyond remanufacturing whenever interactions between lifecycle phases need to be modelled, thus supporting circular economy strategic developments.

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